IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 2, April 2025, pp. 1106~1115
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i2.pp1106-1115

Recommender system for dengue prevention using machine learning

Siriwan Kajornkasirat[1], Benjawan Hnusuwan[1], Supattra Puttinaovarat[1], Kritsada Puangsuwan[1], Nawapon Kaewsuwan[2]
[1]Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani Campus, Surat Thani, Thailand
[2]Faculty of Humanities and Social Sciences, Prince of Songkla University, Pattani Campus, Pattani, Thailand

Article Info

Article history:

Received Nov 23, 2023
Revised Oct 24, 2024
Accepted Nov 14, 2024

Keywords:

Data mining
Dengue hemorrhagic fever
Information systems
Knowledge discovery
Recommender system

ABSTRACT

The study aimed to develop a recommender system for dengue prevention using environmental factors and mosquito larvae data. Data were collected from 100 households in Surat Thani, Thailand using mosquito larval survey in January 2020. Data mining techniques: frequent pattern growth (FP-Growth) and Apriori algorithms were used to find association rules and to compare accuracies for selecting a suitable model. The recommender system was designed as a web application. FP-Growth is more suitable for these data than Apriori algorithm. The factors associated with dengue infection, including community area, densely populated area, and agricultural area. Most areas where mosquito larvae are found are community areas and agricultural areas. *Aedes* larvae were found most in water containers with dark colors and without a lid. *Aedes* larvae were also found in small water jars, large water jars, cement tanks, and plastic tanks. The recommender system should be useful to dengue vector prevention and to health service communities, in planning and operational activities.

Corresponding Author:

Siriwan Kajornkasirat
Faculty of Science and Industrial Technology, Prince of Songkla University
Surat Thani Campus 31 Moo 6, Makhamtia, Muang, Surat Thani-84000, Thailand
Email: siriwan.wo@psu.ac.th

1. INTRODUCTION

Dengue is a mosquito-borne viral disease transmitted by female mosquitoes mainly of the species *Aedes aegypti* and, to a lesser extent, *Ae. albopictus* [1]. There are around 2.5 billion people worldwide infected with dengue fever [1], [2]. It is found in tropical and sub-tropical countries, and it becomes an epidemic during the rainy season [2]. Dengue symptoms range from mild to fatal if not treated promptly [2]. Symptoms begin with headaches, muscle pain, and bone pain, in the three phases of the illness, namely fever phase, shock phase, and recovery period [3]. Dengue fever still plays a significant role in daily lives, with climate and moisture affecting the dengue epidemic that starts from June to August and will be more severe when the temperature exceeds 24 °C to 30 °C [4] but cannot spread if the temperature is below 16 °C [2], [4].

Since 1953 to 1964, dengue fever has spread in many countries in Southeast Asia and in the Asia Pacific, namely in the Philippines, Thailand, Vietnam, Singapore, and in Kolkata, India [5]. In 2018, a dengue epidemic occurred in Thailand, with 41,094 cases and 48 deaths. The number of dengue cases in Thailand increases every year, mostly among school-age and adults those aged between 10 and 34 years old [6]. The majority of deaths can found in Central and Southern regions in Thailand. The provinces with the highest dengue incidence rates are Phuket, Krabi, Phang Nga, Samut Sakhon, and Bangkok [7].

In 2018, dengue situation in Surat Thani province started from January to June during the rainy season. Surat Thani is ranked the 14th province in Thailand by its 462 dengue cases, and the highest 142 cases of dengue by district were in Muang District [8]. In 2019, the dengue hemorrhagic fever epidemic in Thailand had 49,174 cases in the first half of July, with 64 deaths (in the rainy season). Therefore, provincial public health officials were ordered to carry out a campaign to residents, advising them to destroy mosquito-breeding grounds in and around their houses [8]. There were 17.91 incidences per 100,000 population in Surat Thani province, and 30 dengue incidences in Muang District [8]. Surat Thani has an increasing trend of dengue cases.

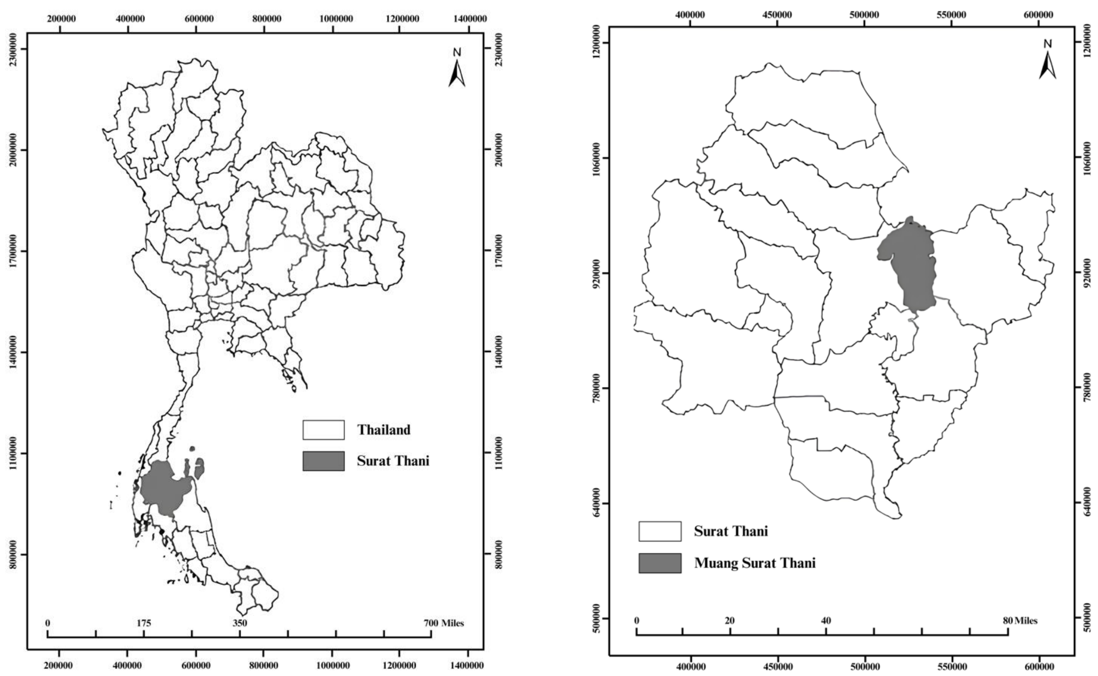
The recommender system was developed to assist in various fields such as medical, food, tourism, as well as epidemiology [9]. Schmidt *et al.* [10] found that the breeding of large numbers of mosquito larvae happens in areas with low to moderate population density and the access to tap water in communities has reduced the number of mosquito larvae. Also, Getachew *et al.* [11] mosquito larvae were found in many old tires that accumulated rainwater, correlates with Philbert and Ijumba [12] found two species of mosquito larvae, *Ae. aegypti* and *Culex sp*. While earlier studies have explored the impact of systems developed to analyze and diagnose whether the user has dengue fever [13], they have not explicitly addressed their influence on the environment. Therefore, containers with standing rain water serve as breeding grounds of mosquitoes, contributing to the problem of dengue fever. The purpose of this research was to explore the essential factors affecting the incidence of dengue hemorrhagic fever in Surat Thani Province, and to compare optimized algorithms for finding relationships to risk factors of dengue fever, and then to develop a recommender system to users.

2. METHOD

2.1. Data collection

Data on mosquito larvae and water characteristics were collected using a mosquito larval survey. The mosquito larval datasheet consists of general information on houses (i.e., address details, location, and water sources) and mosquito larvae factor data (i.e., types of water containers: water jars, drinking water, vases, ant guards, saucers, lotus basin/aquatic plants, old car tires, leaf sheaths, and unused container scraps, water level, water color, lid, lid type, cleaning frequency) [14]. The mosquito larval surveys covered 100 households in Muang District, Surat Thani Province as shown in Figure 1.

We used a stratified systematic random sampling technique for data collection. The data were divided into 11 subgroups by the 11 sub-districts, namely Talat, Makham Tia, Wat Pradu, Khun Thale, Bang Bai Mai, Bang Chana, Khlong Noi, Bang Sai, Bang Pho, Bang Kung, and Khlong Chanak as see in Figures 1(a) and 1(b). The sample size in each stratum was in proportion to the populations of these sub-districts. The sample in each stratum was selected using a systematic random sampling technique.



(a) (b)

Figure 1. The study site in Surat Thani Province: (a) Thailand map and (b) Surat Thani Province

2.2. Mosquito larvae identification

In the survey, the mosquito larvae species were identified. The equipment for mosquito larvae identification, including plastic/glass cup, colander, latex band, plastic bag, spoon, pen, microscope, and mobile phone. Mosquito larvae were divided into 4 types: *Ae. aegypti, Ae. albopictus, Culex spp., and Anopheles spp.* followed the mosquito larvae key [15].

2.3. Data mining technique

Data mining is used with large amounts of data to find patterns and relationships latent in that dataset [16]. Currently, data mining has many applications in businesses assisting in decision making, in executive science, economy, society, and medical applications [9]. The current study used association rules to find relationships in information, by using methods that are popular and widely used: the Apriori and frequent pattern growth (FP-Growth) algorithms [17]. Apriori is an algorithm for frequent itemset mining and association rule learning over relational databases. This is an algorithm obtained accepted and very popular. Moreover, it is also an algorithm that influences education and develops other algorithms [18]. FP-Growth is the tree-based algorithm of mining the frequent itemsets that reads data from the database 2 times. It works in a divide and conquers way that considerately reduces the size of the subsequent conditional FP-Tree [19].

The risk factors for dengue infection forecasts were sought from the information obtained. These data can be both noisy (possibly due to fundamental errors) or suffer from missing data. The data from different sources were merged avoiding duplication of data, and transformed to facilitate analysis.

The data consists of 10 factors, including sub-district, water container, drinking water, vase, ant guard, saucer, lotus basin/aquatic plants, old car tires, leaf sheath, and unused container scraps. After that, we considered the accuracy of the data for all algorithms. If the algorithm has the most accurate value, we will use it to apply the rules (model) to use as a basis for recommendation [20]. We considered the possibility of the results from association rules for the recommendation. The recommendations made are related to the risk factors for dengue infection, as in 'water containers must be entirely covered with lids' or 'use sand to get rid of the mosquito larva in a waterlogged container'. As mentioned previously, however, there must be rules to know what recommendations to give Figure 2.

In this research, the models were trained using the Weka software version 3.8.3. The data used in the tested models with the total of 727 records. The minimum support was set at 0.1 and the minimum confidence at 0.9 for both FP-Growth and Apriori algorithms.

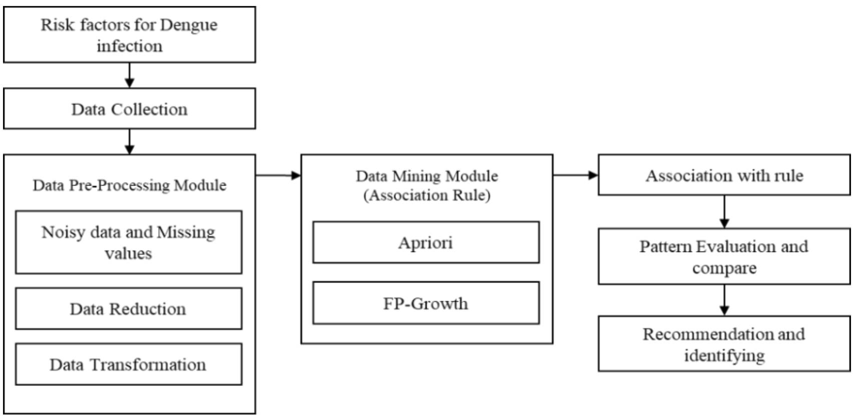


Figure 2. Identifying and using risk factors for dengue infection prediction

2.3.1. Apriori algorithm

This principle allows the algorithm to efficiently discover frequent itemsets by focusing on smaller sets first [18]:

a) Frequent single item identification: the algorithm starts by analyzing the transaction data to find individual items that appear frequently enough. This provides the building blocks for further analysis.
b) Candidate pair generation: using the frequent single items, the algorithm creates pairs (itemsets of size 2) that could potentially be frequent.
c) Candidate pair counting and pruning: each candidate pair is evaluated to check if it appears together frequently enough in the transactions. This involves counting the number of transactions containing both items within the pair. Any candidate pair not meeting the minimum frequency threshold (called "support") is discarded. This process is called pruning, eliminating unlikely frequent itemsets early on.

d) Iterative process for larger itemsets: if any candidate pairs survive the pruning step, they are considered frequent itemsets of size 2. The algorithm then uses these frequent pairs to generate candidate sets of size 3 (triplets). This involves combining the frequent pairs based on the Apriori principle. Similar to step 3, these candidate triplets are evaluated against the minimum support threshold. Frequent triplets are retained, while infrequent ones are pruned.

This iterative process continues:

– Frequent itemsets of a particular size are used to generate candidate sets of the next larger size.
– Each candidate set is evaluated for frequency, and pruning eliminates those not meeting the minimum support criteria.
– The process continues until no more frequent itemsets can be found (i.e., no new candidate sets can be generated based on existing frequent itemsets).

2.3.2. FP-Growth algorithm

FP-Growth adopts a divide-and-conquer strategy. It builds a compressed data structure called an FP-Tree to efficiently store frequent itemsets and their corresponding transactions. This tree structure allows for faster exploration of frequent itemsets [16].

a) Minimum Support Identification: similar to Apriori, FP-Growth first identifies frequent single items based on a minimum support threshold.
b) Building the FP-Tree: frequent items are ordered by their frequency (descending). Each transaction is transformed (infrequent items are removed and remaining frequent items are arranged based on the identified order).

The transformed transactions are inserted into the FP-Tree:

– The root node represents the entire dataset.
– Each subsequent node represents an item and the number of transactions containing that item.
– Nodes are connected by child-parent relationships (a child node represents an item that appears after its parent in a transaction and the frequency of an item is the sum of its own count and the counts of all its child nodes).

c) Mining frequent itemsets: The FP-Tree facilitates efficient exploration of frequent itemsets:

– Each frequent item becomes a starting point for exploring frequent itemsets that include it.
– Follow the frequent item's path in the FP-Tree, summing the support counts along the way.
– Prune any branches with support less than the minimum threshold.

2.4. System analysis

The dengue hemorrhagic fever recommender system (DHFRS) was designed for responsive web design. The user can access the system through a website by using a computer or a mobile device. When used, the system will contact the server to check the access. Then the server will display the information requested through the interface. The server will contact the database to import and display the data through the devices that users use Figure 3.

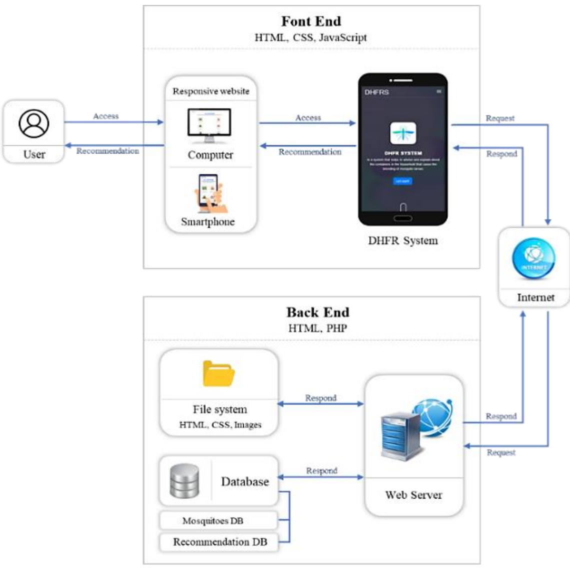


Figure 3. System architecture for DHFR system

DHFRS includes programs written using computer languages such as hypertext markup language (HTML), cascading style sheets (CSS), hypertext preprocessor (PHP), and JavaScript. Apache web server and MySQL are used in the web server and the database management systems, respectively. HTML is responsible for managing the structure and the shape of the website, using CSS to beautify the website adjusting the border color, shape, font styles causing the website to have different elements and aesthetics. JavaScript is used to add functions or add special features to the website, allowing the website to be more interactive with users. PHP, used for server-side scripting, is designed for website development.

3. RESULTS AND DISCUSSION

3.1. Recommender system

The factors analyzed by FP-Growth gave 19 association rules with 0.91-1.00 confidence. The environmental factors (i.e. rivers, canals, rubber plantations, and community areas) and container factors (i.e. big water jar, small water jar, plastic tank, waste container, and cement tank) were associated with the *Aedes sp.* and *Culex sp.* larvae. Water container factors composed of water level at 25-75%, dark colored containers without lids, no cleaning of the container or less than twice a week, and these contributed to *Ae. aegypti*, *Ae. albopictus*, and *Culex sp.* larvae. We found that the results from the Apriori algorithm showed eight association rules with 0.94-1.00 confidence. The environmental factors and water container factors affected *Aedes* larvae. Water container with dark color, water level of 25-50%, without lid and no cleaning were associated with *Aedes* larvae. Moreover, confidence and lift values, which are the probability of value X always occurring with the data value Y by the sequence of events involved which is between 0-1. The FP-Growth gave a value closer to 1 than the Apriori. This means that the FP-Growth is suitable for using to describe the association of the data.

To assess details and compare accuracies of the rules from the analyses the data were graphed. Confidence and lift by FP-Growth and Apriori algorithms are shown in Figures 4 and 5. After the analysis of relationships, we chose to use the relationship rules from the FP-Growth algorithm because they appear suitable for further development in the recommender system due to acquiring much interest within the scientific community.

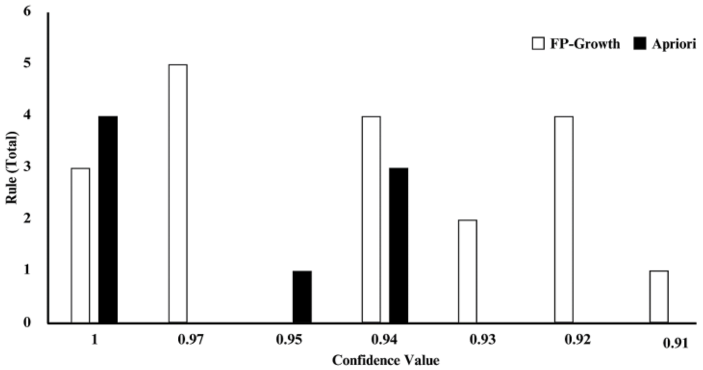


Figure 4. The confidences of FP-Growth and Apriori

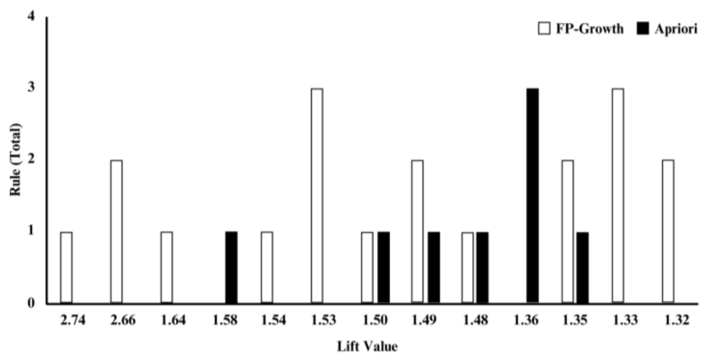
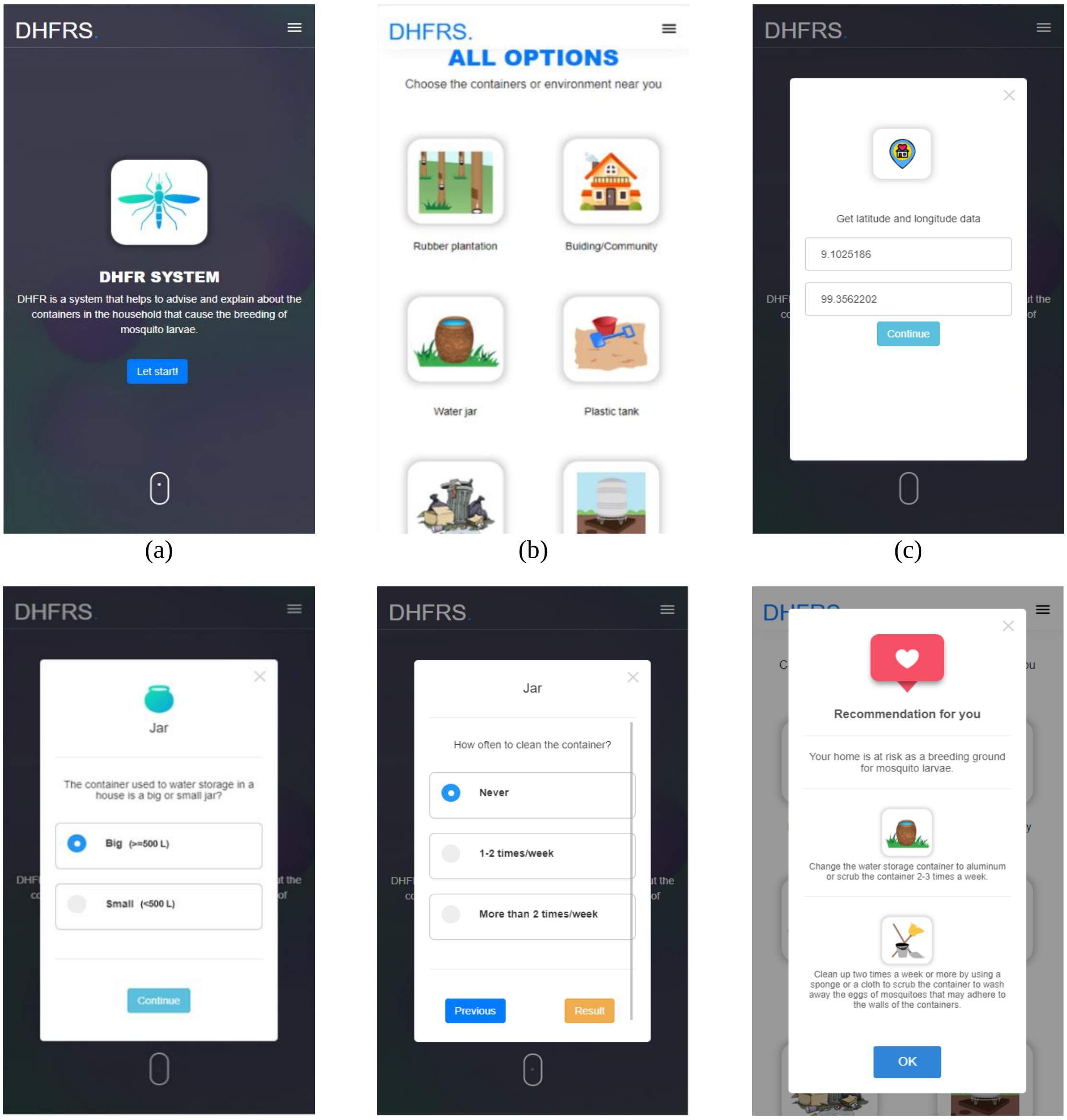


Figure 5. The lifts of FP-Growth and Apriori

The recommender system was designed for ease of use, not made complicated, supporting both computers and mobile phones. Various questions about the environment and household containers are referred to the rules derived from FP-Growth. The system allows users to choose from 8 menus, including rubber plantation, building/community, water jar, plastic tank, unused container scrap, cement tank, river, and channel. Then, users can select the menu and get answer to various questions from the system. When finising the answers, user can click on the result button, and the system will provide recommendations to the user as in Figure 6. Figure 6(a) shows the home page, while Figure 6(b) displays the options for the user to select the container and environment. Figure 6(c) illustrates the location of the study site, and Figure 6(d) provides an example of water containers in and around the house. Figure 6(e) depicts the cleaning frequency of the water containers, and Figure 6(f) presents an example of the system's recommendation. Since March 2020, DHFRS has been available online at URL http://www.s-cm.site/dhf.



(a) (b) (c)
(d) (e) (f)

Figure 6. User interface of the DHFRS: (a) home, (b) menu, (c) get location, (d) question in system, (e) result button, and (f) recommendation

3.2. Users satisfaction assessment

A questionnaire was created to inquire about the satisfaction level regarding DHFRS. It was divided into three parts, which are general information of respondents; system satisfaction information; and suggestions. The data were collected on 12 June 2020 via Google Form, and 55 responses were received. The results are summarized in Table 1.

Table 1. The mean and standard deviation of the user satisfaction regarding the DHFR system

Evaluation topic	$\bar{x}$ ±SD
The system is easy to use	4.727±0.560
Format and method of presenting information	4.745±0.480
System work process	4.745±0.480
Accuracy and precision	4.764±0.470
The menu design is not complicated	4.727±0.489
Data currentness	4.855±0.356
Convenience using the system	4.855±0.356
Suitability for using the system	4.800±0.404
Satisfaction in use	4.818±0.434
System capabilities and utilization	4.764±0.470

3.3. Discussion

This study investigated the essential factors affecting the incidence of dengue hemorrhagic fever in Surat Thani Province, and to compare optimized algorithms for finding relationships to risk factors of dengue fever, and then to develop a recommender system to users. This study is the first attempt to applied data mining techniques with a recommendation system using risk factors for dengue prevention. Dengue is a significant public health problem worldwide. It has been estimated that about 2.5 billion individuals, a staggering 40% of the world population, inhabit areas where there is a risk of transmission of dengue fever, and that the disease burden has increased at least fourfold in the last three decades [21].

Nowadays, information technology (IT) is widely used and applied to health science research [22] and globally computers are used to store, retrieve, transmit, and manipulate data or information. Another way to approach the data is by employing data mining. Currently, data mining is prevalent due to its tremendous success in various applications. The ever increasing complexity of technology and improvements has created new challenges for the data mining world to handle various challenges [23] correlated with Chen *et al.* [20] studied the use of data mining in many medical tasks, such as in disease diagnosis and a treatment recommendation system, diagnosis of dementia among the elderly people [24], and to the diagnosis of balance disorders, as well as to provide recommendations for appropriate information to be requested at each step of the diagnostic process.

From the results in this research, the confidence level of the model exceeds 90 percent, which is an acceptable level [25] correlated with Wongkoon *et al.* [14] found that small water-holding containers were the breeding source of *Ae. Aegypti.* In order that Jomon and Valamparampil [26] mentioned that the significant habitats of mosquito were at rubber plantations, including various containers such as coconut shells, various types of containers, and tree holes. Breeding has been observed in drains, ground pools, rock pools, canals, paddy fields, tanks, and other minor habitats [27]. We found that the Apriori algorithm showed eight association rules with 0.94-1.00 confidence. The environmental factors and water container factors affected *Aedes* larvae. Water container with dark color, water level of 25-50%, missing a lid, and cleaning frequency affected *Aedes* larvae.

Frequent itemset mining leads to the discovery of associations among items. In this research, the two alternative algorithms for generating frequent itemsets were Apriori and FP-Growth. Apriori algorithm is essential in association rule mining. Garg and Gulia [27] found that it has been found useful in many applications like market basket analysis and financial forecasting. In previous research, Thongkam *et al.* [28] used the FP-Growth has been used in the analysis of medical relationships, such as for cancer. Apriori algorithm utilizes a level-wise approach where it will generate patterns first containing 1 item, then 2 items, and 3 items.

Moreover, it will repeatedly scan the database to count the support of each pattern. On the other hand, FP-Growth utilizes a depth-first search instead of a breadth-first search, and uses a pattern-growth approach [28]. We found that the FP-Growth technique could build more association rules than the Apriori algorithm, with a total of 19 rules. The confidence of FP-Growth is 90.00%, with 1.32-2.66 lift that is more significant than 1.00. The FP-Growth was better suited with these data than the Apriori algorithm.

According to Nagao *et al.* [29], the breeding of mosquito larvae occurs during the rainy season, which is consistent with the observation that the number of dengue patients in Thailand generally begins to increase about 1 month after the rain occurs, during the first half of the rainy season [2], [22]. Wongkoon *et al.* [14] studied the related factors for dengue fever, consisting of water containers and surroundings around the house. The data were collected from April to May using a stratified sampling method, at 400 households covering 31 sub-districts. There are mosquito larvae in a cement tank and a large jar. Moreover, many mosquitoes are found in seaside areas. This is consistent with the research of Nagao *et al.* [29] indicating that house breeding mosquito *Aedes* larvae were found in Thailand, causing dengue infection in the area.

Schmidt *et al.* [10] found that the breeding of large numbers of mosquito larvae happens in areas with low to moderate population density and the access to tap water in communities has reduced the number of mosquito larvae. Our study suggests that higher, populated communities have strong breeding of mosquito larvae, and in communities that use tap water there is increased breeding of the mosquito larvae. Even though there is access to tap water in a community, the villagers still use outdoor water containers with or without covers, for rainwater collection or to store water for washing clothes. Also, in the study of Getachew *et al.* [11] mosquito larvae were found in many old tires that accumulated rainwater, correlates with Philbert and Ijumba [12] found two species of mosquito larvae, *Ae. aegypti* and *Culex sp*. Our study demonstrates that the old car tyres did not affect mosquito larvae. However, other factors affecting include plastic buckets and cement tanks. There are 3 types of mosquito larvae that can be found: *Ae. aegypti, Ae. albopictus,* and *Culex sp*. Dengue fever and the spread of mosquito larvae are a threat to the local people.

In areas where dengue is prevalent, standard practices of dengue prevention should be in place regularly to avoid mosquito bites as well as to prevent mosquito breeding. The community members should practice self-protection measures, such as the use of mosquito repellent or mosquito coil, use of bed net, and use of window screens, since these measures help prevent mosquito bites. Meanwhile, Said *et al.* [30] mentioned good practices with domestic water, like covering the water containers and changing the water periodically, should be practiced to reduce mosquito breeding.

4. CONCLUSION

Recent observations suggest that the FP-Growth is more suitable for the data in this study than Apriori algorithm. The factors associated with dengue infection, including community area, densely populated area, and agricultural area. The container factors included big jars, small jars, plastic tanks, waste containers, and cement tanks. Water level of 25-75%, dark colored container without lid, no cleaning of the container, or cleaning less often than twice a week contributed to having *Ae. aegypti*, *Ae. albopictus*, and *Culex sp.* larvae. The association rules from FP-Growth algorithm were used for the DHFRS. Our findings provide conclusive evidence that this phenomenon is associated with the results displayed to a user instruct in cleaning water containers, as well as based on surroundings of the house inform about safety regarding mosquito larvae and dengue fever infections. However, if we have more information, the appropriate models may change, and the accuracy may also increase. Future studies may explore whether the recommendation system should be useful to dengue vector prevention and to health service communities, in planning and operational activities.

ACKNOWLEDGEMENTS

The authors thank Seppo J. Karrila for constructive comments on the manuscript. The work was supported by Prince of Songkla University, Surat Thani Campus. We also thank the Bureau of Epidemiology, Ministry of Public Health for dengue case data in this study.

REFERENCES

[1] WHO, "Dengue and severe dengue," *World Health Organization*, 2023. Accessed: Mar. 10, 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue
[2] S. Wongkoon, M. Jaroensutasinee, and K. Jaroensutasinee, "Spatio-temporal climate-based model of dengue infection in Southern, Thailand," *Tropical Biomedicine*, vol. 33, no. 1, pp. 55–70, 2016.
[3] Z. Her *et al.*, "Severity of plasma leakage is associated with high levels of interferon gamma-inducible protein 10, hepatocyte growth factor, matrix metalloproteinase 2 (MMP-2), and MMP-9 during dengue virus infection," *Journal of Infectious Diseases*, vol. 215, no. 1, pp. 42–51, 2017, doi: 10.1093/infdis/jiw494.
[4] Z. Xu *et al.*, "Spatiotemporal patterns and climatic drivers of severe dengue in Thailand," *Science of The Total Environment*, vol. 656, pp. 889–901, 2019, doi: 10.1016/j.scitotenv.2018.11.395.
[5] L. Bravo, V. G. Roque, J. Brett, R. Dizon, and M. L'Azou, "Epidemiology of dengue disease in the Philippines (2000–2011): a systematic literature review," *PLoS Neglected Tropical Diseases*, vol. 8, no. 11, Nov. 2014, doi: 10.1371/journal.pntd.0003027.
[6] T. Seujam, "Dangers of dengue fever during the rainy season," *Dataxet Limited*, 2023. Accessed: Mar. 13, 2023. [Online]. Available: https://www.ryt9.com/s/iq01/2869467
[7] Thai Health Promotion Foundation, "The domicile of people with dengue fever," *Thai Health Promotion Foundation*, 2023. Accessed: Feb. 13, 2023. [Online]. Available: http://www.thaihealth.or.th/Content/41872.html
[8] STPHO, "Weekly dengue data," *Surat Thani Provincial Health Office*, 2023. Accessed: Mar. 08, 2023. [Online]. Available: http://www.stpho.go.th
[9] Y. Goksen, M. Eminagaoglu, and O. Dogan, "Data mining in medical records for the enhancement of strategic decisions: a case study," *Scientific Bulletin - Economic Sciences*, vol. 10, no. 1, pp. 135–44, 2011.
[10] W. P. Schmidt *et al.*, "Population density, water supply, and the risk of dengue fever in Vietnam: cohort study and spatial analysis," *PLoS Medicine*, vol. 8, no. 8, Aug. 2011, doi: 10.1371/journal.pmed.1001082.
[11] D. Getachew, H. Tekie, T. Gebre-Michael, M. Balkew, and A. Mesfin, "Breeding sites of *aedes aegypti*: potential dengue vectors in Dire Dawa, East Ethiopia," *Interdisciplinary Perspectives on Infectious Diseases*, vol. 2015, pp. 1–8, 2015, doi: 10.1155/2015/706276.

[12] A. Philbert and J. N. Ijumba, "Preferred breeding habitats of *aedes aegypti* (diptera-culicidae) mosquito and its public health implications in Dares Salaam, Tanzania," *E3 Journal of Environmental Research and Management*, vol. 4, no. 10, pp. 344–51, 2013.
[13] T. R. Bin Razak, R. A. Wahab, and M. H. Ramli, "Dengue notification system using fuzzy logic," *Proceeding - 2013 International Conference on Computer, Control, Informatics and Its Applications: "Recent Challenges in Computer, Control and Informatics", IC3INA 2013*, pp. 231–235, 2013, doi: 10.1109/IC3INA.2013.6819179.
[14] S. Wongkoon, M. Jaroensutasinee, and K. Jaroensutasinee, "Locations and religious factors affecting dengue vectors in Nakhon Si Thammarat, Thailand," *Walailak Journal of Science and Technology*, vol. 2, no. 1, pp. 47–58, 2005.
[15] S. Wongkoon, "*Aedes aegypti* and *Aedes albopictus* larval distribution in Thailand," *Ph.D. Thesis,* Department of Computational Science, Walailak University, Nakhonsrithammarat, Thailand, 2011. [Online]. Available: https://opac.wu.ac.th/bibitem?bibid=b00119862
[16] J. Han, M. Kamber, and J. Pei, *Data mining: concepts and techniques*, 2022, doi: 10.1016/C2009-0-61819-5.
[17] EMC Education Services, *Data science and big data analytics: discovering, analyzing, visualizing and presenting data*, Hoboken, USA: Wiley, 2014.
[18] R. Agrawal, T. Imieliński, and A. Swami, "Mining association rules between sets of items in large databases," *ACM SIGMOD Record*, vol. 22, no. 2, pp. 207–216, 1993, doi: 10.1145/170036.170072.
[19] A. M. Al-Badani and B. M. Al-Maqaleh, "Efficient mining of frequent itemsets using improved FP-growth algorithm," *International Journal of Applied Information Systems (IJAIS)*, vol. 12, no. 14, pp. 15–20, 2018.
[20] J. Chen, K. Li, H. Rong, K. Bilal, N. Yang, and K. Li, "A disease diagnosis and treatment recommendation system based on big data mining and cloud computing," *Information Sciences*, vol. 435, pp. 124–149, 2018, doi: 10.1016/j.ins.2018.01.001.
[21] S. Shah, R. Tyagi, and P. Shah, "Case study & review on dengue fever: an emerging public health issue," *International Journal of Perceptions in Public Health*, vol. 2, no. 1, pp. 24–30, 2017, doi: 10.29251/ijpph.2017124.
[22] S. Wongkoon, M. Jaroensutasinee, and K. Jaroensutasinee, "Weather factors influencing the occurrence of dengue fever in Nakhon Si Thammarat, Thailand," *Tropical Biomedicine*, vol. 30, no. 4, pp. 631–641, 2013.
[23] S. H. Bhojani and N. Bhatt, "Data mining techniques and trends-a review," *GJRA - Global Journal for Research Analysis*, vol. 5, no. 5, pp. 252–254, 2016.
[24] L. B. Moreira and A. A. Namen, "A hybrid data mining model for diagnosis of patients with clinical suspicion of dementia," *Computer Methods and Programs in Biomedicine*, vol. 165, pp. 139–149, 2018.
[25] K. Lai and N. Cerpa, "Support vs confidence in association rule algorithms," in *OPTIMA 2001 - Conference of the ICHIO (The Chilean Operations Research Society)*, 2001.
[26] K. Jomon and T. Valamparampil, "Medically important mosquitoes in the rubber plantation belt of central Kerala, India," *Southeast Asian Journal of Tropical Medicine and Public Health*, vol. 45, no. 4, 2014.
[27] R. Garg and P. Gulia, "Comparative study of frequent itemset mining algorithms apriori and FP growth," *International Journal of Computer Applications*, vol. 126, no. 4, pp. 8–12, 2015, doi: 10.5120/ijca2015906030.
[28] J. Thongkam, V. Sukmak, and P. Sukmak, "Performance comparison of apriori and FP-growth techniques in generating association rules to prostate cancer," *Journal of Applied Informatics and Technology*, vol. 1, no. 2, pp. 103–111, 2019, doi: 10.14456/jait.2018.9.
[29] Y. Nagao, U. Thavara, P. Chitnumsup, A. Tawatsin, C. Chansang, and D. Campbell-Lendrum, "Climatic and social risk factors for *aedes* infestation in rural Thailand," *Tropical Medicine and International Health*, vol. 8, no. 7, pp. 650–659, 2003, doi: 10.1046/j.1365-3156.2003.01075.x.
[30] M. F. F. Said, H. Abdullah, and N. Abdul Ghafar, "Dengue prevention practices among community in dengue hotspot area," *International Journal of Community Medicine and Public Health*, vol. 5, no. 11, pp. 4664–9, 2018, doi: 10.18203/2394-6040.ijcmph20184553.

BIOGRAPHIES OF AUTHORS

Siriwan Kajornkasirat received the Ph.D. degree in computational science from Walailak University, Thailand, in 2011. She has participated in Ph.D. research experience in Deakin University, Australia funded by the Royal Golden Jubilee Ph.D. Program (RGJ-Ph.D. Program). In 2014, she was invited for STEM education workshop under the international visitor leadership program (IVLP). This is a program of the U.S. Department of State with funding provided by the U.S. Government. Currently, she is Assistant Professor at the Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani, Thailand. Her research interests include data science, computing science, advanced analytics online, STEM education, smart farming, internet of things (IoT), smart health, digital marketing, and e-marketing for tourism. She can be contacted at email: siriwan.wo@psu.ac.th.

Benjawan Hnusuwan received the Master of Science Program in applied mathematics and computing science, Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani Campus, Thailand. Currently, she is a systems analyst at Addpay Service Point Co., Ltd. Her current research interests include data science, smart health, internet of things (IoT), and machine learning. She can be contacted at email: tumhnusuwan@gmail.com.

Supattra Puttinaovarat received the B.B.A. degree (Hons.) and the M.S. degree in management of information technology from the Prince of Songkla University, Thailand, and the Ph.D. degree in information technology from the Suranaree University of Technology, Thailand. She is currently an Associate Professor with the Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani Campus, Surat Thani, Thailand. Her research interests include flood modeling, geographic information systems, remote sensing, digital image processing, and machine learning. She can be contacted at email: supattra.p@psu.ac.th.

Kritsada Puangsuwan received the B.Eng. degree in electronics engineering technology from King Mongkut's University of Technology North Bangkok (KMUTNB), Bangkok, in 2010, the M.Eng. degree in computer engineering from Prince of Songkla University (PSU), Songkhla, in 2012, and the Ph.D. degree in computer engineering from Prince of Songkla University (PSU), Songkhla, in 2017. He joined the Department of Electrical Engineering, Faculty of Engineering, Rajamangala University of Technology Srivijaya, Songkhla, in 2016, as a Lecturer. In 2020, he joined the Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani Campus, Surat Thani, Thailand. His current research interests include electronics and computer technology for agriculture, microwave and high frequency heating, internet of things (IoT), image processing, and renewable energy. He can be contacted at email: kritsada.pu@psu.ac.th.

Nawapon Kaewsuwan received the B.B.A. degree in computer information system from Rajamangala University of Technology Tawan-Ok, Thailand, in 2012 and the M.I.ED. degrees in educational technology from King Mongkut's Institute of Technology Ladkrabang, Thailand, in 2015. Currently, he is lecturer at the Department of Information Management, Faculty of Humanities and Social Sciences, Prince of Songkla University, Pattani Campus. His research interests include information science, information and knowledge management, technology administration, and educational techonology adoption and utilization. He can be contacted at email: nawapon.k@psu.ac.th.